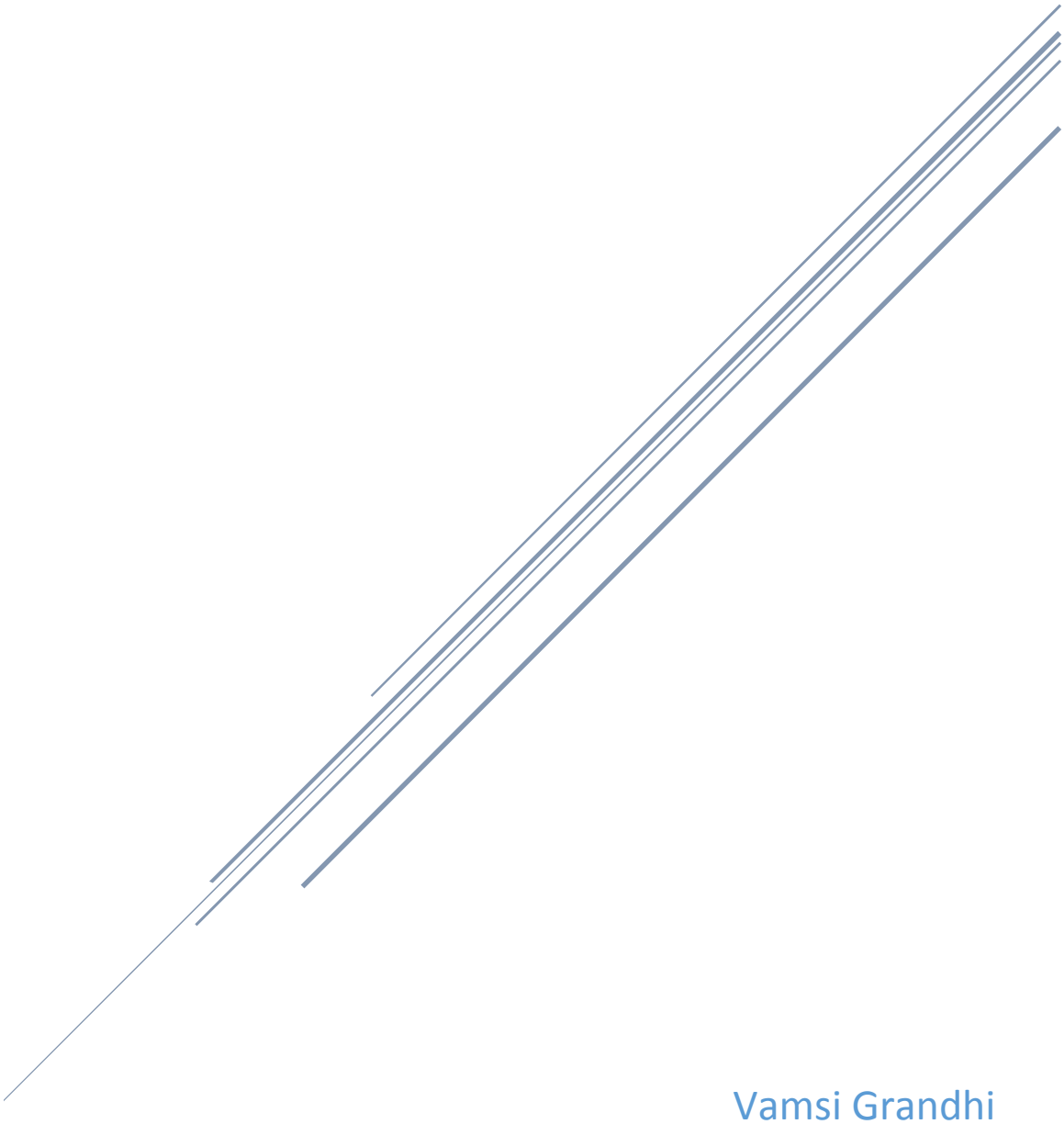
CASE STUDY

Credit Default



Vamsi Grandhi

Contents

Business Objective

1. Exploratory analysis on credit default data set
2. Model to identify the default status for next month based on historical data

Data

The given data for **30,000** individuals has their transaction history for 6 months (April to September), demographics, education, and payment history. The given data has following columns.

X1: Amount of the given credit (NT dollar)
X2: Gender (1 = male; 2 = female).
X3: Education (1 = graduate school; 2 = university; 3 = high school; 4 = others)
X4: Marital status (1 = married; 2 = single; 3 = others).
X5: Age (year)
X6 - X11: History of past payment.
X12-X17: Amount of bill statement (NT dollar)
X18-X23: Amount of previous payment (NT dollar)

Exploratory analysis:

Data Cleansing (part a)

All the variables in the given data are continuous and they are converted into categorical, nominal & continuous variables based on basic knowledge.

The given data has been segregated as **14** continuous variables and **9** categorical variables

Continuous Variables	Categorical & Nominal Variables
1. X1: Amount of the given credit card 2. X5: age 3. X6-X11: History of payment 4. X12-X17: Amount of bill statement 5. X18-X23: Amount of previous payment	1. X2: Gender 2. X3: Education 3. X4: Marital Status

Missing data: There is **no** missing data in either of the continuous or categorical variables.
Data Imputation: The following procedures has been adopted to handle unmentioned levels of categorical variables
Credit default proportion: only **22%** of given records are default and other are non-defaulters indicating level of imbalance.

Data Imputation for categorical & nominal variables

Gender: No imputation has been done on gender variable and there are **more females credit card holders** compared to males.

Gender	No of credit card holders
female	18112
male	11888

Education: The data has more levels of education such as 0,4,5,6 apart from mentioned ones i.e; high school, graduate school, university & others. The levels **0,4,5,6** along with category **"other"** are mentioned as **"unknown"**. There are more number **of university graduated** credit card holders compared to others

Data before imputation:

Education level	No of credit card holders
University	14030
Graduate school	10585
High school	4917
5	280
others	123
6	51
0	14

Data after Imputation:

Education level	No of credit card holders
University	14030
Graduate school	10585
High school	4917
Unknown	468

Marital Status: The data has an extra level of marital status "0" apart from mentioned ones i.e; single, married & others. The levels **0,** along with category **"other"** are mentioned as **"others"**. There are more **single** credit card holders compared to married & others

Data before imputation:

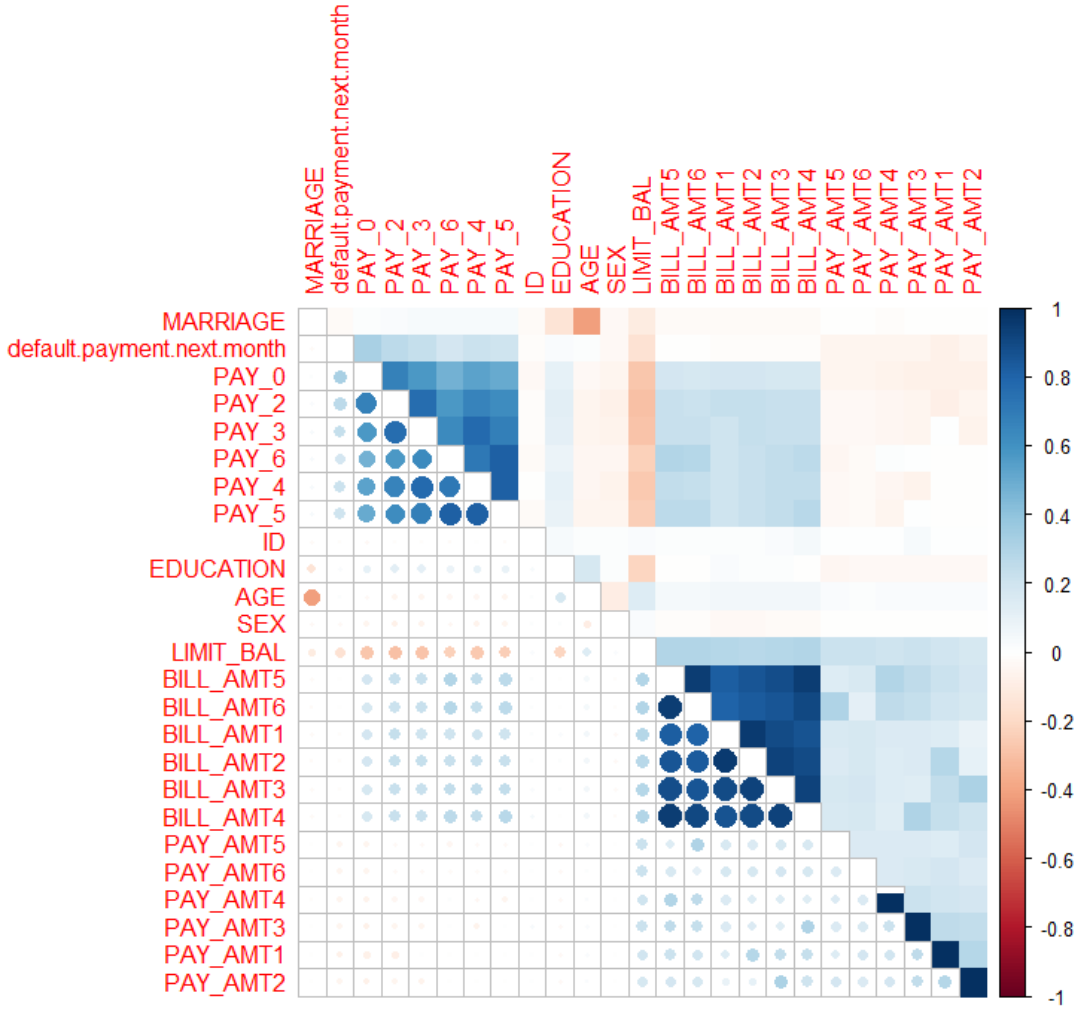
Marital Status	No of Credit card holders
single	15964
married	13659
others	323
0	54

Data after imputation:

Marital Status	No of Credit card holders
single	15964
married	13659
others	377

Relationship between variables

The relationship between variables is described in the following section. A mixed correlation plot between variables is given below. It is quite evident from the plot that payment made by individual is **very likely** correlated with billing amount i.e; **an individual pay very less than the billing amount.** The correlation plot is given below.



Relationship between gender & education

Female credit card holders are highly educated compared to male

Education	Female	Male
University	8656	5374
Graduate School	6231	4354
High School	2927	1990
Unkown	298	170
Total	18112	11888

Relationship between gender & default payment status

24% of males are credit card defaulters against their counterpart's i.e: females who constitute for **20%**

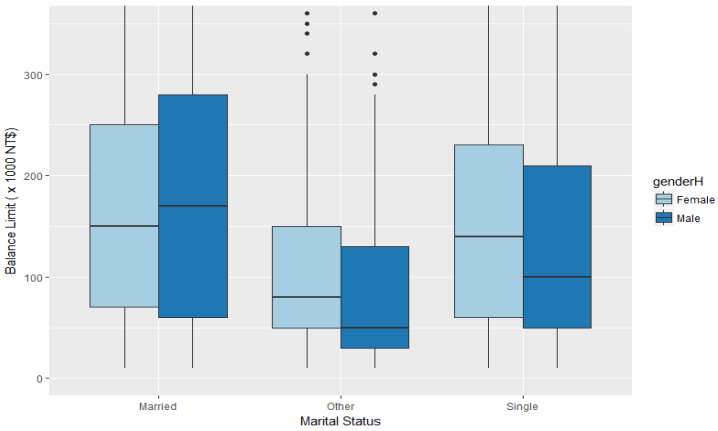
Gender	Credit Card default status (0)	Credit Card default status (1)	Proportion of credit card defaulters
female	14349	3763	20%
male	9015	2873	**24%**

Relationship between gender, education & default payment status

There are number of male & female **university graduate** credit card defaulters compared to other educational backgrounds

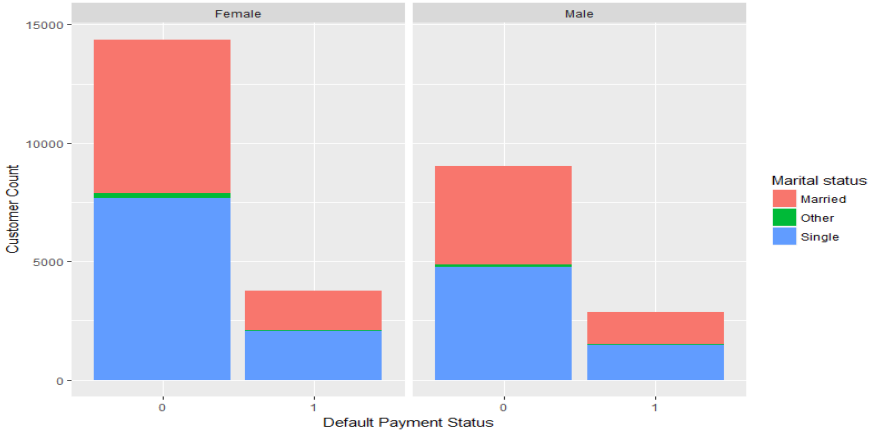
Relationship between sex, marital status & Balance limit

Married males & females have higher balance limit compared to single and other males & females and their variance is also high compared to other groups. Below is the figure which illustrates this phenomenon.



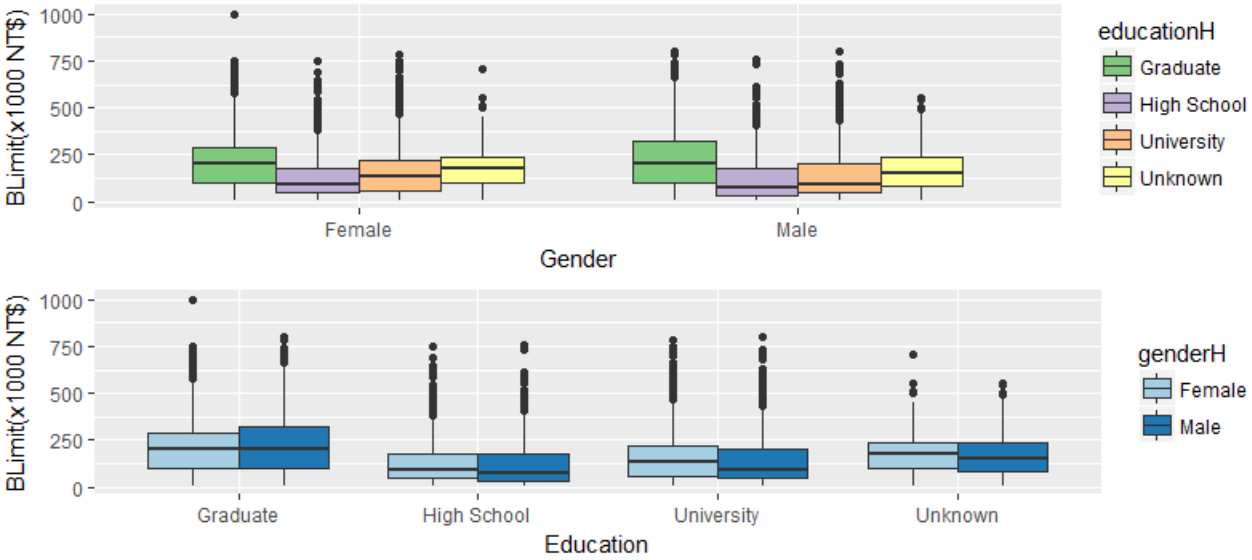
Relationship between sex, marital status & default payment status

Single females & males are tend to be more default compared to married males & females. Below is the figure which illustrates this phenomenon.



Relationship between sex, education & Balance limit

Both male &female **graduates** followed by **university** male & female students have higher balance limit compared to high school & unknown education level. The below given images explain the phenomenon



Feature Engineering

Some variables have been generated out of the data to understand more about the patterns of default & for building the model in predicting credit default. The feature engineered variables are as follows:

a. Working state
b. Average_repayment
c. Average_bill_amount
d. Bill amount to balance limit ratio
e. Amount owed
f. Repayment ratio
g. Age_bin
h. No of missing payments

Working state

An individual is considered to be working if sum of all the **payment history status is <=0** i.e; he/she paid either due payment or full payment. The calculation is described as follows:

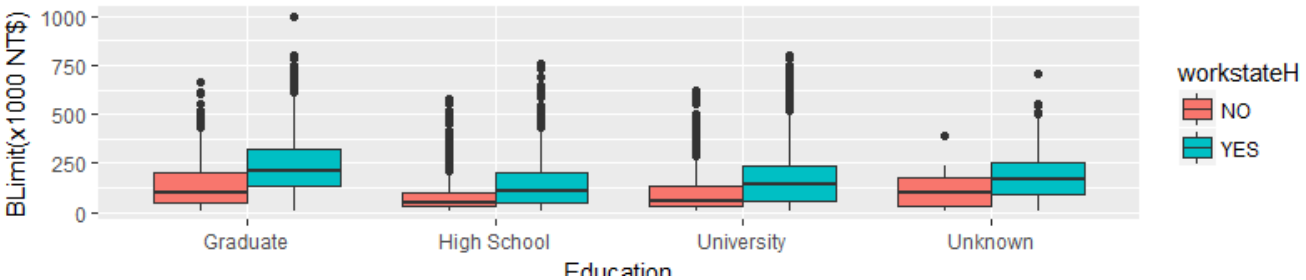
Working status - yes if sum (pay_0 + pay_2 + pay_3 + pay_4 + pay_5 + pay_6) < 0

Working status - NO if sum (pay_0 + pay_2 + pay_3 + pay_4 + pay_5 + pay_6) > 0

Relationship between working state, education & Balance limit

The following inferences can be made from the below figure:

1. Credit cards have been issued to working people
2. Balance limit of working graduates, high school pass outs compared to non-working individuals.



Average Repayment

It's an average repayment made by an individual for the 6 months (April – September) in the given data.

Average repayment = Average (Previous payments (X18-X23))

Average Bill amount

It's an average bill amount made by an individual for the 6 months (April – September) in the given data.

Average repayment = Average (Bill statement (X12-X17))

Bill amount to balance limit ratio

The bill amount to balance limit ratio for an individual is calculate as

Bill amount to balance limit ratio = Average bill amount / Balance limit

Amount owed

The remaining amount (billing amount – paid amount) that is owed by an individual to banks. It is calculated as **amount_owed = sum(bill statement(X12-X17)) – sum(previous payments(X18-X23))**

Repayment ratio

It is calculated as ratio of average repayment made to average billing amount for an individual. It is calculated as **repayment ratio = average (previous payments(X18-X23)) / average (bill statement(X12-X17))**

Age bin

A nominal variable has been created by binning continuous age variable ranging from **0-80** into eight buckets.

Age Group	Bin number
0-10	1
11-20	2
21-30	3
31-40	4
41-50	5
51-60	6
61-70	7
71-80	8

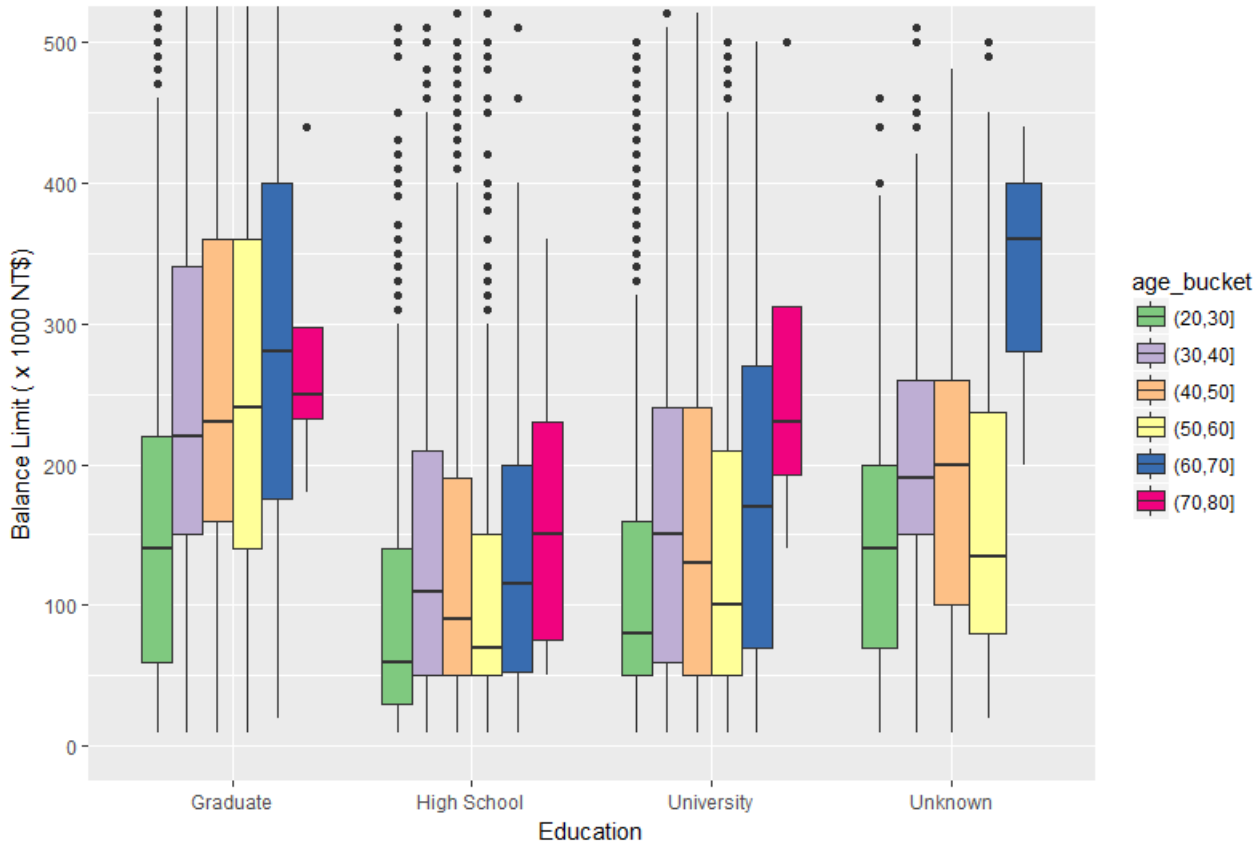
No of missing payments

If payment status of any individual for the six months (april – September) is greater than equal to 1 i.e; payment delayed by one month is considered as missing payment

No of missing payments = countif (pay_0:pay_6,">0")

Relationship between age bin, education & balance limit

It is quite evident that university graduate of all age groups have higher balance limit compared to other educational backgrounds.



Data cleansing part b

Outlier detection with bill amount to balance limit ratio

Some unusual billing amount patterns have been detected for individuals with bill amount to balance limit ratio **greater than 1.25.**

Their monthly bills increased suddenly **twice or three** from the previous month and far greater than balance limit and their repayment to bill ratio is of **average 0.08** and there are in total of **79 candidates**.

ID	Bill_amt1	Bill_amt2	Bill_amt3	Bill_amt4	Bill_amt5	Bill_amt6	Repayment /bill ratio	Bill amount_balance limit ratio
673	99568	32326	31840	37075	37662	36904	0.276	1.52
921	471814	478380	395612	386295	356206	352257	0.033	1.69
971	42784	41009	44267	47149	48497	14774	0.104	1.98
1678	90231	90647	92309	93880	99418	101392	0.042	1.89

Out of **79 candidates 57 are non-defaulters** which is illogical and they are removed from the data considering them as outliers.

Out of **57 individuals 20 are non-working** and they have an average billing amount of **10, 4987 USD** and have an average repayment ratio of **0.08**

Outlier detection with age group, repayment to bill amount ratio, working state & education

62 Individuals within age group of 20-30 & non –working high school graduates with an average repayment ratio less than 0.04 are **not considered as defaulters**. With intuition these records have been removed from data considering them as outliers.

Modelling

As mentioned earlier that the data being highly unbalanced the data has been balanced using **smote technique** ,**under & over sampling techniques** and the same data has been used for model building **using naïve bayes model, & XG Boost.**

Data Cleansing

The records which have Inf, NaN/ NA repayment ratio & bill amount to bill limit ratio have been removed prior to model building.

```
#removing any NA, NAN & inf values
data_model <- data_model[is.finite(data_model$repayment_ratio),]
```

Data partitioning

70% of data has been used for training and 30% for model testing for naïve bayes & Xg boost algorithms

```
##########  partitioning data for training & testing###########
set.seed(36)
trainIndex  =  createDataPartition(data_model$default.payment.next.month, p = .7, list = FALSE, times = 1)
ntrain_bay = data_model[trainIndex,]
ntest_bay = data_model[-trainIndex,]
```

Data Balancing

The training data has been balanced using the following techniques

Oversampling technique:

This technique is used to balance data by replicating the minority class by **3 times**

```
> train.over <- oversample(train.task,rate=3) ### making minority class 3 times
> table(getTaskTargets(train.over))

    0     1
15886 13272
```

Under sampling technique:

This technique is used to balance data by randomly selecting **50% of majority class.**

```
> train.under <- undersample(train.task,rate = 0.5) # keep only 50% of majority class
> table(getTaskTargets(train.under))

   0    1
7943 4424
```

Smote technique:

This technique is used to balance data by replicating the minority class by 4 times and considering 5 nearest neighboring data points.

```
> train.smote <- smote(train.task,rate = 4,nn = 5) #### considering 5 nearest neighbours for data points
> table(getTaskTargets(train.smote))

    0     1
15886 17696
```

Data Modelling

The unbalanced, over sampled, under sampled & smote data have been used for building XG boost & navie bayes model.

Steps in building the model

The unbalanced, over sampled, under sampled & smote training data has been used to build the above mentioned models using **5 fold cross validation technique** and found that **unbalanced data** has **higher accuracy and sensitivity**. **Sensitivity** is considered as performance metric as it's important to predict the exact number of defaulters with high accuracy.

Testing the models:

The models built through unbalanced data has been used to test the data and the results are given in the following table.

Model	**naïve bayes**		**XG Boost**	
Metrics	Accuracy %	Sensitivity %	Accuracy %	Sensitivity %
Unbalanced (train.task)	**77.55**	**48.65**	**82.43**	**68.19**
Oversample (train.over)	65.75	35.44	79.17	55.18
under sample (train.under)	60.41	32.18	76.99	47.4
Smote (train.smote)	42.36	25.84	80.74	58.31

From the above table it's quite evident that XG boost is giving better results on unbalanced dataset compared to navie bayes algorithm.